Synopsis

Ph.D in Computer Science

Cervical Cancer Detection and Classification in Pap smear Images using Enhanced Deep Learning Models

Submitted by

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INTRODUCTION

Cervical Cancer (CC) is considered as most common type of cancer only prone to females. Meanwhile, developed nations have major impacting factors such as, the advancement of screening techniques and vaccination systems. Thus, leaving behind the poor resource environment with the burden disparity between females is quite intense. Owing to CC, the escalating death has been witnessed among females in world. However, the development of advanced technology majorly focuses on cost effectiveness, sensitive and rapid CC screening (Al-Batah. Et.al. 2022). According to WHO 2022 (Cervical cancer. World Health Organization), cervical cancer is considered as fourth most common cancer in women globally with around 6,60,000 new cases and around 3,50,000 deaths in 2022. Based on Indian Council of Medical Research's National Cancer Registry Programme (ICMR-NCRP) 2023, it is observed that the number of cervical cancer cases in India was more than 3.4 lakh which is currently more prevalent (The Economic Times, February 2024).

Correspondingly, contagious causes are responsible for 25% of cancer cases and 15% of cancers are due to viral causes. In this context, a number of various viruses could contribute to steps involved in carcinogenic processes. Among such viruses, Human PapillomaVirus (HPV) considered as a prominent, due to 305 contagious cancer causing cell. In the CC and in many other tumors, RNA’s non-coding single strand known as miRNAs is short and plays a critical role. In contrast, HPVs are being persistent and responsible for high-risk oral and various malignancies, which affect neck, head, anus, vagina, penis, vulva and particularly cervix; However, the viral infections are especially responsible for all CCs (Sompawong et.al 2019).

Meanwhile, cervix is the lower part of uterus in the female reproductive system which is 2 to 3 cm in length and in roughly cylindrical shape. The central, narrow cervix canal runs with complete length, associating the uterine cavity and vagina lumen. The opening of cervix into uterus is known as internal os whereas, an opening to the vagina, known as external os. The cervix lower part is called as the vaginal portion of cervix which bulges into the vagina top. The cervix is made up of various types of microscopic cells.

Furthermore, individual cells are in limited lifespan and separated to produce new cells during requirement by the body. Sometimes, the process is disturbed and the cells divide when

new cells are not essential, or it may develop abnormal cells. The growth of abnormal cells can lead to malignancy. The diverse changes in cervical cells were known as dysplasia.

The different stage of CC is predicted using 5 stage system which is mentioned below in detail.

- **Stage 0:** The presence of pre-cancerous cells.
- **Stage 1:** The evolution ofcancer cells in the cervix deeper tissues from surface that affects uterus and lymph nodes.
- **Stage 2:** Advancement of cancer cells beyond uterus and cervix, but fails to reach pelvis walls or the vagina's lower part.
- **Stage 3:** Presence of cancer cells in lower area of vagina.
- **Stage 4:** Possible infection in rectum or bladder and can infect outer pelvis. Later, it affects distant organs (Huang et.al. 2020).

HPV-based insistent infection is a significant etiologic factor for the CC. HPV is sexually transferred infection; however, many HPV infections eradicate the immune system in human body. Some genotypes with high oncogenicity are named as hrHPV. Commonly, HPVs are classified through their tropism to cutaneous epithelia and mucosal. However, low-risk HPVs could cause benign skin warts and genital. Furthermore, HPVs are presented in more than 95% of CCs. Henceforth, the suggestion of treatment techniques and results are highly dependent on prediction of disease stage for CC patients.

Importance of CC Detection

CC Detection is accomplished by asymptomatic test and screening of females to detect the pre-cancerous modifications which is further harmful if not treated. However, screening or detecting is highly preferred to track the modifications in working of regular organ system. If females with abnormalities are detected, the further predictions and possible treatment is prescribed to prevent the progression of cancer in early stages. This includes numerous tests for successful screening of CC where Pap smear is highly preferred. It is considered as the golden standard test which is preferred for huge population to decrease the mortality and incidence of the CC.

The existing trends of AI such as Deep Learning and Machine Learning are highly utilized for CC detection. At present, the rapid advancements of technology in computer technological innovation and clinical innovation, different diagnostic and screening strategies depends on Computer-aided Design (CAD) architectures.

Even though, AI-based solution (C. Nakisige et.al. 2021) is prevalent in the field of cervical cancer detection, achieving higher accuracy is still a challenging due to the presence of false alarm rate. Machine learning (M. Mehmeeod et.al. 2021) algorithms are prone to data misinterpretation (Al Mudawi et.al. 2022) due to imbalanced data (Newaz A et.al.2022 a). In addition, training classification model using small dataset limits the performance such as accuracy, precision, recall and f-score (Devi.S et.al 2023a). It is necessary to address such shortcomings in present research for cervical cancer detection and classification.

Problem Statement

Given an image dataset D containing multiple classes (Da, Db, ...,Dn) with a set of features F, the research problem is to develop enhanced preprocessing and segmentation techniques that can effectively classify the images from D into O, where O contains various classes. The deep learning techniques are enhanced to classify cervical cancer images and non-cervical cancer images and assessed based on the performance metrics such as accuracy, precision, recall, and F-measure.

Objectives

In this section, the primary and several secondary objectives for cervical cancer detection and classification in proposed research is explained in further.

Primary Objective

To enhance the identification and classification of cervical cancer in pap smear image using Deep Learning techniques that are capable of accurately categorizing cell samples from pap smear tests into normal or abnormal consisting of various classes by integrating image preprocessing, image segmentation, and feature-based classification methods, and evaluate the performance in terms of accuracy, recall, F1-score and precision.

Secondary Objectives

- To preprocess and segment the image dataset using Contrast Limited Adaptive Histogram Equalization based Diffusion Stop Function and Topographic Weibull Bounding Segmentation for further multi-class classification using Radiance and Variance enabled Deep Learning Neural Networks for CC cell detection.
- To combine Adaptive Diffusion Function –Histogram Equalization based preprocessing technique and Improved Weighted –Fuzzy C Means based segmentation for further CC cell detection and classification using Restricted Boltzman Machine in pap smear images.
- To combine Adaptive Diffusion Function –Dragonfly Optimization based preprocessing technique and Improved Weighted –Fuzzy C Means –Grasshopper Optimization Algorithm based segmentation in image dataset for further CC cell detection and classification using Deep-Convolutional Neural Network with ReLu.
- To compare the performance of all three model with other state-of-the-art method to find the best among them for cervical cancer cell detection with higher performance.

METHODOLOGY

Research methodology shows the mechanism involved in three different proposed models for better CC detection. Figure 1 illustrates the process involved in the proposed mechanism for the classification of CC cells.

Pre-processing: The aim of this step is to enhance the image quality for subsequent analysis and it is accomplished using techniques such as noise reduction, contrast enhancement, and color normalization. The visibility of important features is improvised while suppressing irrelevant information that could interfere with the analysis.

Segmentation: Following the pre-processing technique, segmentation technique isolates regions of interest focusing only cervical cells from the background. Some advanced methods such as thresholding, edge detection, or region-based approaches are employed. The accuracy of segmentation directly impacts the performance of the entire model, as it determines which parts of the image are further analyzed.

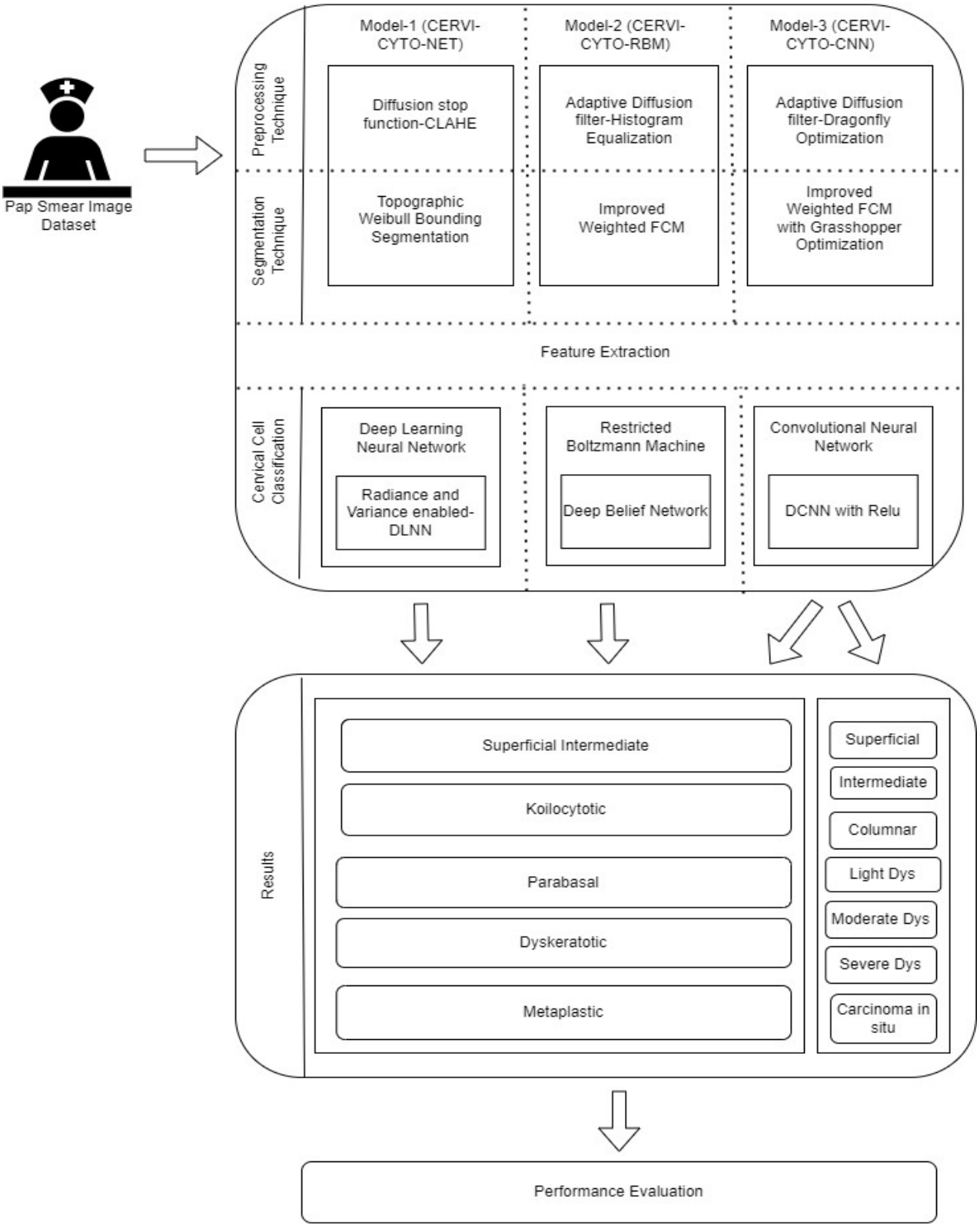

Figure.1. Overall flow of all three models

Feature Extraction: After segmentation, feature extraction is typically applied to simplify the representation of the images by reducing their dimensionality. It involves identifying and quantifying key characteristics of the cells, such as shape, size, texture, and color. The extracted features should capture the essential information which is helpful in distinguishing different cell types and conditions.

Cervical Cell Classification: The final step is to classify the cells based on the extracted features. Machine learning classifiers such as support vector machines (SVM), random forests, neural networks or Deep Learning classifiers could be used. In this research, deep learning techniques such as Deep Convolutional Neural Networks (DCNNs), Deep Learning Neural Network (DLNN), Deep Belief Network (DBN) are particularly effective as they can automatically learn hierarchical feature representations from the data.

Each of these steps plays a crucial role in the overall performance of the model. Pre-processing ensures that the input data is of high quality. Segmentation allows the model to focus on the most relevant parts of the image. Feature extraction reduces computational complexity and helps in identifying the most discriminative features. Finally, classification leverages these features to make predictions about the presence or absence of cervical cancer cell.

Designing and tuning each stage in every model is required to achieve high accuracy in classifying cervical cells, which is vital for effective screening and early detection of cervical cancer. The study introduces three distinct models for classifying cervical cells into single cell and multicell categories. The multicellcategory consist of five classes: superficial intermediate, Koilocytotic, Parabasal, Dyskeratotic, and Metaplastic. The single cell category is further divided into seven classes: Superficial, Intermediate, Severe_Dysplastic, Moderate_dysplastic, Light_dysplastic, Columnar, andCarcinoma_in_situ.

Further, each model incorporates more sophisticated techniques to enhance the accuracy and reliability of cervical cell classification, which is crucial for the early detection and treatment of cervical cancer. The use of various pre-processing, segmentation, and classification methods demonstrates a comprehensive approach to tackle the challenges presented by the complex nature of medical images. These three models are used for effective classification of CC cells for

preventing life-threatening situations. Eventually, the efficacy of the models are evaluated by using metrics such as,

- Accuracy
- F1 score
- Recall
- Precision

MODEL 1 - AUTOMATED DIAGNOSIS OF CC BY USING TWBS AND RVDLNN IN PAP SMEAR IMAGE(CERVI-CYTO-NET)

Initially, the datasets are pre-processed by using the DSF-CLAHE algorithm in which the colors of images are transformed, and the contrast of the input images are improved. CLAHE divides the image into numerous sub-regions called tiles, and histogram equalization is applied to each of the divided images; then, by utilizing bilinear interpolation, neighboring tiles are joined by eliminating the artificial border. After pre-processing, segmentation is proceeded where, TWBS is used. This proposed TWBS encompasses three major steps. In which cell mass is detected from the image using an enhanced SLIC algorithm in stage 1. Nuclei from the image are identified by using local threshold topography in stage 2, and finally, the cytoplasm is detected and marked using Weibull Bounding Segmentation in stage 3. These stages play a crucial role in segmenting the images properly.

After segmentation, feature extraction is performed, where significant features are selected. Eventually, the selected features are given as input to the RV-DLNN model for classifying different types of CC cells, and the efficacy of the proposed model is assessed using different metrics.

MODEL 2- A VERSATILE DETECTION OF CC WITH I-WFCM AND DEEP LEARNING-BASED RBM CLASSIFICATION(CERVI-CYTO-RBM)

In this model, the images are pre-processed using ADF and AHE (Adaptive Histogram Equalization). ADF aids in eliminating unwanted noise from the image with the aim of accomplishing high-quality outcomes, and AHE has been used for enhancing the quality of images more efficiently. After the process of pre-processing, segmentation is proceeded by using

the IW-FCM approach. IW- FCM is implemented for segmenting the RoI (Region of Interest) with the purpose of overcoming uneven forms and the composite nature of histology images. Next, feature extraction is carried out for extracting textural and geometric based features. Finally, classification is performed by using the RBM-DBN model, and it is compared with existing DenseNet201, ResNet50V2, AlexNet, and model 1 (CERVI-CYTO-NET), and the performance of the proposed model is defined by using above mentioned evaluation metrics.

***MODEL 3- NOVEL SEGMENTATION-BASED CC DETECTION USING DEEP CONVOLUTIONAL-BASED NEURAL NETWORK WITH RELU*(CERVI-CYTO-CNN)**

The steps involved in Model 3 are similar to Model 1 and Model 2. However, pre-processing techniques utilized in this model are ADF and dragonfly optimization, where a decision process is performed at the end to identify the ideal edges of the images. Correspondingly, segmentation is done using improved weighted FCM, which is similar to model 2; however, in model 3, improved-weighted FCM is performed using GOA. This incorporation of GOA is achieved by tuning the weighted factor for the clustering center without making the computation a tedious process. In the next step, feature extraction is employed to extract important features. Finally, the classification of the model focuses on utilizing Deep CNN with ReLU activation function, where the Deep CNN model employed in the proposed work encompasses CL (Convolutional Layer), PL (Pooling Layer), FCL (Fully Connected Layer), and softmax layer. Incorporation of these layers along with ReLU aims to enhance the classification of CC cells. Moreover, the proposed mechanism is compared with the existing models such as DenseNet201, ResNet50V2, AlexNet, CERVI-CYTO-NET (Model 1), and CERVI-CYTO-RBM (Model 2) with proposed Deep CNN with ReLU(CERVI-CYTO-CNN). Moreover, the performance of the proposed work is evaluated using different performance metrics for picking best working model among three.

RESULTS AND DISCUSSION

The Herlev dataset consists of 917 single cell images whereas the SIPAKMED dataset consists of 966 multicell images. In both the datasets 70% of the images are used for training and 30% of the images are used for testing the efficiency of the model. The performance of the

proposed models are analyzed using evaluation metrics such as Accuracy, precision, recall, and F1-score. Table 1 describes the proposed Models performance metrics and their values.

Table 1. Performance analysis of proposed Models for Single Cell

Models	Accuracy %	Precision %	Recall %	F1 score %
DenseNet201	87.5	62.2	63.4	63.4
ResNet50V2	90	70	71	73
AlexNet	91	71	78	72
CERVI-CYTO-NET	92.5	72	78	74.5
CERVI-CYTO-RBM	95.3	83.12	77.21	79.5
CERVI-CYTO-CNN	96.7	82.4	82.5	79.5

Table 1 demonstrates the performance of CERVI-CYTO-CNN for single cell classification for cervical cancer detection and attained higher performance than other models. It achieved 9.2%, 6.7%, 5.7%, 4.2%, and 1.4% accuracy, more than DenseNet201, ResNet50V2, AlexNet, CERVI-CYTO-NET, and CERVI-CYTO-RBM, respectively.

Table 2. Performance analysis of proposed Models for Multi Cell

Models	Accuracy %	Precision %	Recall %	F1 score %
DenseNet201	88	63.2	63.8	63.9
ResNet50V2	90	70.5	72.3	73.5
AlexNet	92	78.4	72	74
CERVI-CYTO-NET	93.5	79.6	74.5	76
CERVI-CYTO-RBM	95.3	83.12	77.21	79.5
CERVI-CYTO-CNN	97.8	86.27	84.5	80.25

Table 2 depicts the comparison between the performance of proposed CERVI-CYTO-CNN model with other two models and state-of-art methods. From the above analysis, it is observed that proposed DCNN attained 97.8% accuracy, 86.27% precision, 84.5% Recall, and 80.254% F1 score. i.e., the accuracy achieved by proposed model DCNN is higher by 9.8%, 7.8%, 5.8%, 4.3%, 2.5% more than other models such as DenseNet201, ResNet50V2, AlexNet, RVDLNN, and RBM-DBN models.

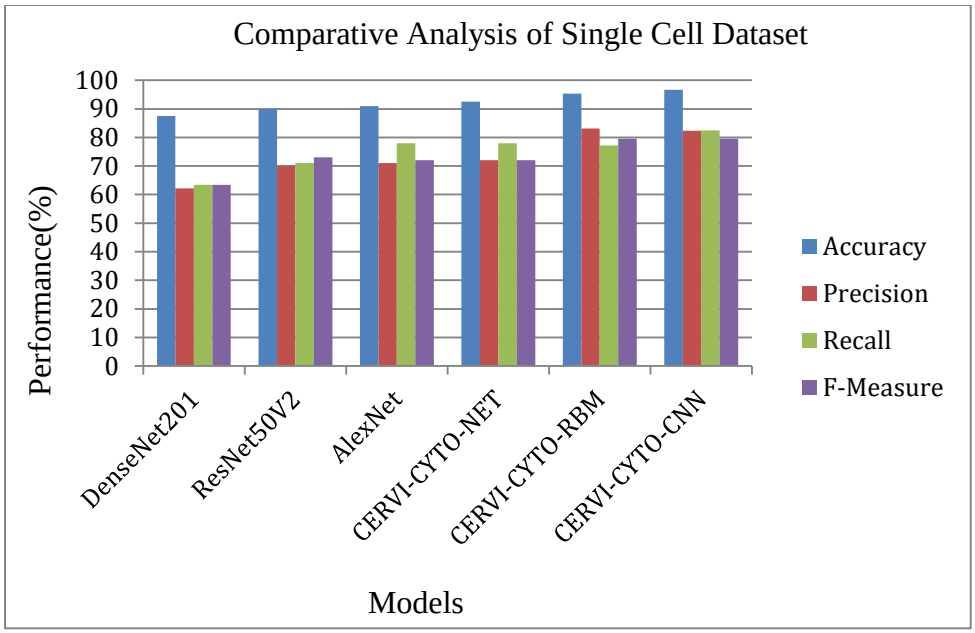

Figure.2 (a).Overall performance of single cell dataset

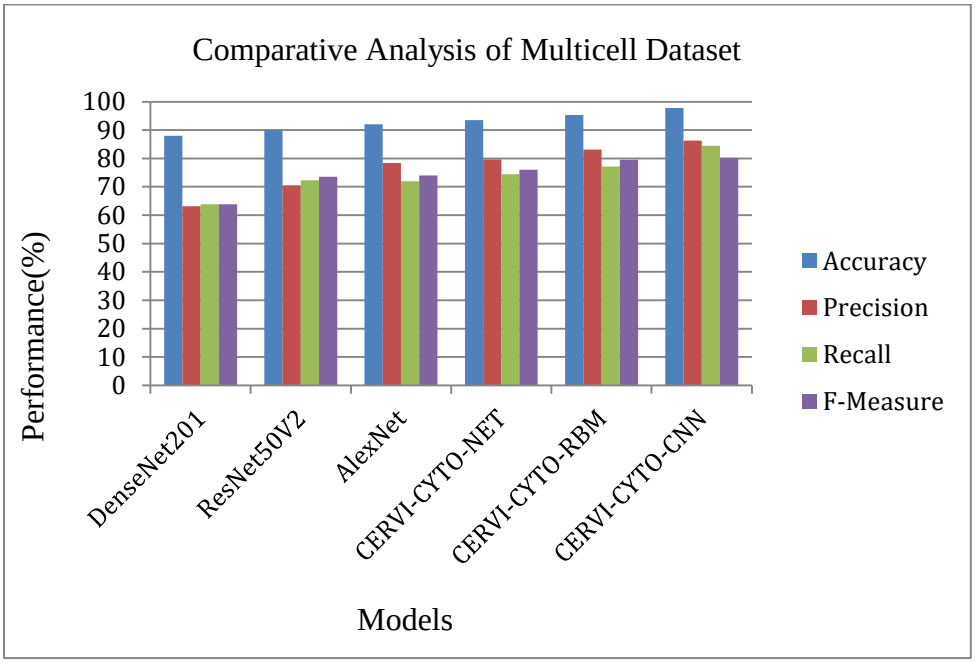

Figure.2 (b).Overall performance of Multi cell dataset

Figure 2 illustrated the performance evaluation of CERVI-CYTO-CNN in terms of single and multi cell classification with other techniques. From Figure 2 (a) and (b), it is observed that performance of CERVI-CYTO-CNN is improved in both single cell and multi-cell classification for cervical cancer detection than others. CERVI-CYTO-CNN with single cell classification

obtained 96.7% accuracy and multi-cell classification obtained* maximum accuracy of 97.8% which is higher and outperforms other techniques in cervical cancer detection.

Conclusion and Future scope

The present study proposed an automatic and enhanced DL-based model for cervical cancer detection and represented the outcomes associated with it. The proposed methodology recognized the use of Deep learning models to analyze cervical cancer cells for classification of destructive and optimistic cervical cancer. It is accomplished using three enhanced DL models namely CERVI-CYTO-NET, CERVI-CYTO-RBM, CERVI-CYTO-CNN using preprocessing, segmentation techniques and are evaluated using two dataset namely Herlevdataset and SIPaKMeD dataset. In model-1, an automatic identification of cervical cancer through TWBS with RVDLNN in pap smear images is proposed. This model combines DSF-CLAHE and Topographic Weibull Bounding Segmentation for pre-processing and segmentation respectively to achieve enhanced performance in radiance and variance enabled DLNN. In model-2, DL model such as RBM-based Deep Belief Network is enhanced using Adaptive Diffusion filter using Histogram Equalization-based preprocessing and improved weighted FCM-based segmentation. Meanwhile, in model-3, combined Adaptive Diffusion Filter-Dragonfly optimization and improved weighted FCM with Grasshopper optimization is implemented for preprocessing and segmentation to optimize the performance of DCNN with Relu for cervical cancer detection and classification. Meanwhile, model-1 achieved an accuracy of 93.5%, precision of 79.6%, recall of 74.5% and F-measure of 76%. Compared to the additional classifiers such as DenseNet201, ResNet50V2, AlexNet, CERVI-CYTO-CNN and CERVI-CYTO-RBM, where CERVI-CYTO-RBM attained higher accuracy of 95.3%. However, CERVI-CYTO-CNN accomplished 96.7% and 97.8% accuracy and comparatively performs better than other prevailing classifiers for both single and multi-cell cervical cancer classification. As a result, model-3 is considered best working model for cervical cancer classification compared to model-1, model-2 and other state-of-art methods based on performance metrics such as accuracy, precision, recall and f-score. In future, the optimization technique such as Particle Swarm Optimization, Ant Colony Optimization can be explored for feature selection to enhance the performance DL models for cervical cancer detection.

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